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14. ABSTRACT
In this project, we have developed various novel collaborative sparse representation methods for multi-sensor classi- fication problem, which take into account correlation as well as complementary information between heterogeneous sensors simultaneously while considering joint sparsity within each sensor's observations. We also robustify our models to deal with the presence of sparse noise and low-rank interference terms. Especially, we observe that incorporating the noise or interfered signal as a low-rank component is essential in a multi-sensor problem when

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Final Report: Robust Multi-Sensor Classification via Jointly Sparse Representation

ABSTRACT

In this project, we have developed various novel collaborative sparse representation methods for multi-sensor classi♀fication problem, which take into account correlation as well as complementary information between heterogeneous sensors simultaneously while considering joint sparsity within each sensor's observations. We also robustify our models to deal with the presence of sparse noise and low-rank interference terms. Especially, we observe that incorporating the noise or interfered signal as a low-rank component is essential in a multi-sensor problem when multiple co-located sources/sensors simultaneously record the same physical event. Essentially, our proposal combines the strengths of multiple ideas: (i) incorporating related information from diff♂erent sources (sensors) to achieve an improvement in the classi♀fication performance; (ii) extracting and suppressing a large, dense and correlated (hence low-rank) signal/noise interference normally appeared in multi-sensor data; and (iii) exploiting prior structure in sparsity representations for e♬fficiency and robustness.

Enter List of papers submitted or published that acknowledge ARO support from the start of the project to the date of this printing. List the papers, including journal references, in the following categories:

(a) Papers published in peer-reviewed journals (N/A for none)

Received		Paper
03/14/2016	15.00	Umamahesh Srinivas, Yuanming Suo, Minh Dao, Vishal Monga, Trac D. Tran. Structured Sparse Priors for Image Classification, IEEE Trans Image Processing, (06 2015): 1763. doi:
03/14/2016	16.00	Umamahesh Srinivas, Yi Chen, Vishal Monga, Nasser M. Nasrabadi, Trac D. Tran. Exploiting Sparsity in Hyperspectral ImageClassification via Graphical Models, IEEE GEOSCIENCE AND REMOTE SENSING LETTERS, (05 2013): 505. doi:
03/14/2016	17.00	Qing Qu, Nasser M. Nasrabadi, Trac D. Tran. Abundance Estimation for Bilinear Mixture Modelsvia Joint Sparse and Low-Rank Representation, IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, (07 2014): 4404. doi:
03/14/2016	18.00	Xiaoxia Sun, Qing Qu, Nasser M. Nasrabadi, Trac D. Tran. Structured Priors for Sparse-Representation-BasedHyperspectral Image Classification, IEEE GEOSCIENCE AND REMOTE SENSING LETTERS, (07 2014): 1235. doi:
03/14/2016	19.00	Bryan T. Bosworth, Jasper R. Stroud, Dung N. Tran, Trac D. Tran, Sang Chin, Mark A. Foster. High-speed flow microscopy using compressed sensing with ultrafast laser pulses, Optics Express, (04 2015): 10521. doi:
03/14/2016	20.00	Xiaoxia Sun, Nasser M. Nasrabadi, Trac D. Tran. Task-Driven Dictionary Learning for HyperspectralImage Classification with Structured SparsityConstraints, IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, (08 2015): 4457. doi:
03/14/2016	21.00	Nam H. Nguyen, Trac D. Tran. Robust Lasso With Missing and GrosslyCorrupted Observations, IEEE TRANSACTIONS ON Information Theory, (04 2013): 2036. doi:
03/14/2016	22.00	Nam H. Nguyen, Trac D. Tran. Exact Recoverability From Dense CorruptedObservations via l1-Minimization, IEEE TRANSACTIONS ON Information Theory, (04 2013): 2017. doi:

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Number of Papers published in peer-reviewed journals:

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Received		Paper
10/02/2013	7.00	Nam Nguyen, Trac Tran. Robust Lasso With Missing and Grossly Corrupted Observations, IEEE TRANSACTIONS ON Information Theory, (04 2013): 0. doi:
10/02/2013	8.00	Nam Nguyen, Trac Tran. Exact Recoverability From Dense CorruptedObservations via L1-Minimization, IEEE TRANSACTIONS ON Information Theory, (04 2013): 0. doi:
10/02/2013	10.00	Yi Chen, Nasser M. Nasrabadi, Trac D. Tran. Hyperspectral Image Classification viaKernel Sparse Representation, IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, (01 2013): 0. doi:
10/02/2013	11.00	Umamahesh Srinivas, Yi Chen, Vishal Monga, Nasser M. Nasrabadi, Trac D. Tran. Exploiting Sparsity in Hyperspectral ImageClassification via Graphical Models, IEEE GEOSCIENCE AND REMOTE SENSING LETTERS, (05 2013): 0. doi:

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Peer-Reviewed Conference Proceeding publications (other than abstracts):

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01/13/2013	4.00	Nam H. Nguyen,, Nasser M. Nasrabadi,, Trac D. Tran. Robust Lasso with missing and grossly corruptedobservations, Twenty-Fifth Annual Conference on Neural Information Processing Systems (NIPS 2011). 06-DEC-11, . : ,
01/13/2013	6.00	Umamahesh Srinivas,, Yi Chen,, Vishal Monga,, Nasser M. Nasrabadi,, Trac D. Tran. DISCRIMINATIVE GRAPHICAL MODELS FORSPARSITY-BASED HYPERSPECTRAL TARGET DETECTION, IEEE International Geoscience and Remote Sensing Symposium (IGARSS2012). 22-JUL-12, . : ,
01/13/2013	5.00	Umamahesh Srinivas, , Vishal Monga,, Yi Chen, , Trac D. Tran. Sparsity-based Face Recognition usingDiscriminative Graphical Models, IEEE Asilomar Conference on Signals, Systems and Computers. 06-NOV-11, . : ,
10/02/2013	9.00	Nam H. Nguyen, Nasser M. Nasrabadi, Trac D. Tran. MULTI-SENSOR JOINT KERNEL SPARSE REPRESENTATION FOR PERSONNELDETECTION, 20th European Signal Processing Conference (EUSIPCO 2012). 31-AUG-12, . : ,
10/02/2013	12.00	Yuanming Suo, Minh Dao, Trac Tran, Umamahesh Srinivas, Vishal Monga. HIERARCHICAL SPARSE MODELING USING SPIKE AND SLAB PRIORS, 38th International Conference on Acoustics, Speech, and Signal Processing (ICASSP2013). 31-MAY-13, . : ,
10/02/2013	13.00	Minh Dao, Yuanming Suo, Sang Chin, Trac Tran. VIDEO FRAME INTERPOLATION VIA WEIGHTED ROBUST PRINCIPAL COMPONENT ANALYSIS, 38th International Conference on Acoustics, Speech, and Signal Processing (ICASSP2013). 31-MAY-13, . : ,

TOTAL: **6**

Number of Peer-Reviewed Conference Proceeding publications (other than abstracts):

(d) Manuscripts

Received		Paper
01/13/2013	1.00	Nam H. Nguyen, , Nasser M. Nasrabadi,, Trac D. Tran. Robust Multi-Sensor Classification via Joint Sparse Representation, Information Fusion (03 2012)
01/13/2013	2.00	Nam H. Nguyen,, Trac D. Tran. Exact recoverability from dense corruptedobservations via L1 minimization, IEEE TRANSACTIONS ON INFORMATION THEORY (09 2011)
01/13/2013	3.00	Nam H. Nguyen,, Trac D. Tran. Robust Lasso with missing and grossly corrupted observations, IEEE TRANSACTIONS ON INFORMATION THEORY (11 2011)
03/14/2016	14.00	Minh Dao, Nam H. Nguyen, Nasser M. Nasrabadi, Trac D. Tran. Collaborative Multi-sensor Classification via Sparsity-based Representation, IEEE Trans Signal Processing (07 2015)

TOTAL: **4**

Number of Manuscripts:

Books

Received Book

TOTAL:

Received Book Chapter

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Patents Submitted

L. H. Nguyen and T. D. Tran, METHOD AND SYSTEM FOR ESTIMATION AND EXTRACTION OF INTERFERENCE NOISE FROM SIGNALS, US Application No. 14/452902.

Patents Awarded

L. H. Nguyen and T. D. Tran, Method and system for removal of noise in signal, U.S. Patent No. 9,172,476. Oct. 2015.

Awards

U. Srinivas, Y. Chen, V. Monga, N. M. Nasrabadi, and T. D. Tran, "Discriminative graphical models for sparsity based hyperspectral target detection," in Proc. IEEE Int. Geoscience and Remote Sensing Symposium, Munich, Germany, July 2012. Best Student Paper Award. IEEE Mikio Takagi Student Prize (First Prize) 2012.

Trac D. Tran, IEEE Fellow for contributions in multi-rate and sparse signal processing, 2014

Graduate Students

NAME	PERCENT_SUPPORTED	Discipline
Xiaoxia Sun	0.50	
Nam H. Nguyen	0.50	
Yuanming Suo	0.50	
FTE Equivalent:	**1.50**	
Total Number:	**3**	

Names of Post Doctorates

NAME	PERCENT_SUPPORTED
FTE Equivalent:	
Total Number:	

Names of Faculty Supported

NAME	PERCENT_SUPPORTED	National Academy Member
Trac D. Tran	0.08	
FTE Equivalent:	**0.08**	
Total Number:	**1**	

Names of Under Graduate students supported

NAME	PERCENT_SUPPORTED	Discipline
Xioaxia Sun	0.50	ECE
Yuanming Suo	0.50	ECE
Nam H. Nguyen	0.50	ECE
FTE Equivalent:	**1.50**	
Total Number:	**3**	

Student Metrics

This section only applies to graduating undergraduates supported by this agreement in this reporting period

The number of undergraduates funded by this agreement who graduated during this period: 2.00

The number of undergraduates funded by this agreement who graduated during this period with a degree in science, mathematics, engineering, or technology fields:...... 0.00

The number of undergraduates funded by your agreement who graduated during this period and will continue to pursue a graduate or Ph.D. degree in science, mathematics, engineering, or technology fields:...... 0.00

Number of graduating undergraduates who achieved a 3.5 GPA to 4.0 (4.0 max scale):...... 0.00

Number of graduating undergraduates funded by a DoD funded Center of Excellence grant for Education, Research and Engineering:...... 0.00

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The number of undergraduates funded by your agreement who graduated during this period and will receive scholarships or fellowships for further studies in science, mathematics, engineering or technology fields:...... 0.00

Names of Personnel receiving masters degrees

NAME

Total Number:

Names of personnel receiving PHDs

NAME
Nam H. Nguyen
Yuanming Suo

Total Number: 2

Names of other research staff

NAME	PERCENT_SUPPORTED

FTE Equivalent:

Total Number:

Sub Contractors (DD882)

Inventions (DD882)

Scientific Progress

We are trying to combine data collected from multiple low-cost sensors co-located in a dense sensor network to improve classification result in event-detection applications. In other words, we take advantage of highly-correlated and coupling information from multiple different, yet co-located, sources (sensors) recording the same physical event, to improve the overall detection/classification accuracy.

The main challenge that we face in this project comes from noises in the data collected from low-cost low-power primitive sensors. Sometimes, there is an outrageous level of noise (amplitude-wise, duration-wise, bandwidth-wise…). In fact, we occasionally stumble into sensors that completely failed during the entire data collection process. We have to deal with outliers and missing/incomplete data as well. Another major challenge is that sensors are multi-modal and heterogeneous. How can we properly fuse information in this complicated set-up? Finally, the availability (or lack thereof) of well-labeled data sets is also a major issue.

We are able to take advantage of a few recent ideas from the compressed sensing / sparse representation community – namely joint-sparsity, group-sparsity, and the sparse-representation-based classification framework – and successfully combine them with two of our own novel ideas – optimization with class-specific priors and modeling structured noise / interference with a low-rank model. Our expertise in dictionary design, compressed sensors design, and optimization in sparse recovery also helps. We are able to advance the state of the art classification accuracy by 10-15% in a very challenging data sets from an automatic border patrol application.

Technology Transfer

Collaborations with ARL Researchers:

Dr. Nasser M. Nasrabadi, ARL Fellow, now Professor of CSEE at West Virginity University

Lam Nguyen, RF Signal Processing and Modeling Branch, Sensors and Electronic Devices Directorate, ARL

Dr. Anders Sullivan, Branch Chief, RF Signal Processing and Modeling Branch, Sensors and Electronic Devices Directorate, ARL

Dr.Heesung Kwon, Image Processing Branch, Sensors and Electronic Devices Directorate, ARL

Dr. Tung-Duong Tran-Luu, Acoustic and EM Sensing Branch, Sensors and Electronic Devices Directorate, ARL

Dr. Nasrabadi and Lam Nguyen are active collaborators. We have published together multiple times on this project over the past 3 years.
Dr. Sullivan, Dr. Kwon and Dr. Tran-Luu gave us data sets relevant to this project: ultra wideband synthetic aperture radar data sets, hyperspectral data sets, and multi-sensor acoustic data sets. We are actively collaborating even now after the project has ended. Our collaborators above have access to our algorithm designs, source codes, and published papers.

In our research, we propose various novel collaborative sparse representation methods for multi-sensor classification problem, which take into account correlations as well as complementary information between heterogeneous sensors simultaneously while considering joint sparsity within each sensor's observations. We also robustify our models to deal with the presence of sparse noise and low-rank interference terms. Especially, we observe that incorporating the noise or interfered signal as a low-rank component is essential in a multi-sensor problem when multiple co-located sources/sensors simultaneously record the same physical event. Essentially, our proposal combines the strengths of multiple ideas: (i) incorporating related information from different sources (sensors) to achieve an improvement in the classification performance, (ii) extracting and suppressing a large, dense and correlated (hence low-rank) signal/noise interference normally appeared in multi-sensor data, and (iii) exploiting prior structure in sparsity representations for efficiency and robustness. Our associated data model is:

$$\begin{aligned} \underset{\mathbf{A},\mathbf{L}}{min} \quad & \mathcal{F}_S(\mathbf{A}) + \lambda_L \left\| \mathbf{L} \right\|_* \\ s.t. \quad & \mathbf{Y}^m = \mathbf{D}^m \mathbf{A}^m + \mathbf{L}^m \quad (m = 1, ..., M) \end{aligned} \tag{1}$$

where M is the total number of sensors with M corresponding sparsifying dictionaries $\mathbf{D}^1, \mathbf{D}^2, ..., \mathbf{D}^M$; $\mathbf{Y} = [\mathbf{Y}^1, \mathbf{Y}^2, ..., \mathbf{Y}^M]$ is the concatenated set of measurements where each sample subset $\mathbf{Y}^m$ collected from the sensor m $(m = 1, ..., M)$ consists of T observations $\mathbf{Y}^m = [\mathbf{y}_1^m, \mathbf{y}_2^m, ..., \mathbf{y}_T^m]$; $\mathbf{A} = [\mathbf{A}^1, \mathbf{A}^2, ..., \mathbf{A}^M]$ contains the sparse codes with certain sparsity structure; and $\mathbf{L} = [\mathbf{L}^1, \mathbf{L}^2, ..., \mathbf{L}^M]$ is the low-rank noise/interference. The nuclear matrix norm $\left\| \mathbf{L} \right\|_*$, defined as the sum of all singular values of the matrix $\mathbf{L}$: $\left\| \mathbf{L} \right\|_* \doteq \sum_i \sigma_i(\mathbf{L})$, is a convex-relaxed surrogate of the rank [1, 2]; while $\mathcal{F}_S(\mathbf{A})$ is a convex structured sparsity-promoting function that incorporates collaborative structured-sparsity constraints both within each sensor and across multiple sensors; and $\lambda_L > 0$ is a weighting parameter balancing the two regularization terms.

It is noted that the model (1) is different from our previous model [3] when we developed the multi-sensor joint sparse representation fusion model in the presence of gross but sparse noise penalized by an ℓ_1-norm regularization. In our current approach, we study another critical corruption case: the dense and large but correlated noise, so-termed low-rank interference $\mathbf{L}$. This scenario is normally observed when the recorded data is the superimpositions of target signals with interferences which can be signals from external sources (such as a car running through, a helicopter flying nearby, or any radio-frequency interference), the underlying background that is inherently anchored in the data, or any pattern noise that remains stationary during signal transmission. These interferences normally have correlated structure and appear as a low-rank signal-interference/noise. In a veritable manner, the model with the low-rank interference may be more appropriate for the multi-sensor dataset since the sensors are spatially co-located and data samples are temporally recorded, thus any interference from external sources will affect similarly on all the multiple sensor measurements, hence justifying the low-rank property.

In order to exploit complementary features from multiple measurements, we incorporate different structures on the concatenated coefficient matrix $\mathbf{A}$ through the penalized function $\mathcal{F}_S(\mathbf{A})$ which can yield in element-wise-sparse, row-sparse or group-sparse within each sensor and across multiple sensors, or any hierarchical tree-sparsity structure that simultaneously penalize several sparsity levels in a combined cost function. In the most general form, our model searches for the group-and-row sparse structure representation among all sensors and low-rank interference simultaneously and is termed as multi-sensor group-joint sparse representation with low-rank interference (MS-GJSR+L):

$$\begin{aligned} \underset{\mathbf{A},\mathbf{L}}{min} \quad & \left\| \mathbf{A} \right\|_{1,q} + \lambda_G \sum_{c=1}^{C} \left\| \mathbf{A}_c \right\|_F + \lambda_L \left\| \mathbf{L} \right\|_* \\ s.t. \quad & \mathbf{Y}^m = \mathbf{D}^m \mathbf{A}^m + \mathbf{L}^m \quad (m = 1, ..., M) \end{aligned} \tag{2}$$

where $\mathbf{A}_c = [\mathbf{A}_c^1, \mathbf{A}_c^2, ..., \mathbf{A}_c^M]$ is the concatenation of sub-coefficient matrices $\mathbf{A}_c^m$'s of all sensor m's $(m = 1, ..., M)$ induced by the labeled indexes corresponding to class c; and $\lambda_G \geq 0$ is the weighting parameter of the group constrain. The optimization of (2) can be interpreted as follows: the first term $\left\| \mathbf{A} \right\|_{1,q}$ with $q > 1$ is a norm calculated by taking an ℓ_q-norm across the rows (observations) and then

Set	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Sensors	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{1-2}	S_{5-7}	S_{1-4}	S_{1-7}	$S_{1-2,5-9}$	S_{1-9}

Table 1: List of sensor combinations.

an ℓ_1-norm along the columns, hence encourages row-wise sparsity within and among all sensors; the group regularizer defined by the second term tends to minimize the number of active groups in the same coefficient matrix $\mathbf{A}$; and the third term penalizes the nuclear norm of the interference as afore-discussed. In succession, the model promotes a two-sparsity-level model: group-sparse and row-sparse in the combined coefficient matrices, in parallel with extracting the low-rank interference appearing in all measurements all together. We also propose a fast and efficient algorithm based on alternative direction method to solve for (2) and its convergence to optimal solution is guaranteed.

The optimization (2) is a general framework that can be simplified to introduce other methods. In fact, if we let $\lambda_G = 0$ then (2) becomes multi-sensor joint sparse representation with low-rank interference (MS-JSR+L) framework that extracts the low-rank approximation in $\mathbf{L}$ while promoting sparsity at row level in the concatenated matrix $\mathbf{A}$ at the same time. Furthermore, if we eliminate the presence of $\mathbf{L}$ (i.e. set $\mathbf{L}$ to be a zero matrix in all optimization iteration), then it reduces to the MS-JSR framework where a joint-sparse constrain is advocated through out all sensors without taking care of the interfered noise. Finally, if the number of sensor is further set to $M = 1$, we simply have a joint-sparse representation with a single sensor alone.

Model (2) can even be further extended into kernelized models which relies on sparsely representing a test sample in terms of all the training samples in a feature space induced by a non-linear kernel function. The kernelized model of (2) (namely MS-KerGJSR+L) can be written as:

$$\begin{aligned} \underset{\mathbf{A},\mathbf{L}}{min} \quad & \|\mathbf{A}\|_{1,q} + \lambda_G \sum_{c=1}^{C} \|\mathbf{A}_c\|_F + \lambda_L \|\mathbf{L}_\phi\|_* \\ s.t. \quad & \Phi(\mathbf{Y}^m) = \Phi(\mathbf{D}^m)\mathbf{A}^m + \mathbf{L}_\phi^m \ (m = 1, ..., M) \end{aligned} \tag{3}$$

where Φ is an implicit mapping that maps any set of vectors onto a higher dimensional space, possibly infinite, and $\mathbf{L}_\phi$ is the additive low-rank interference in the kernal feature domain. Note that in general the mapping function Φ is not explicitly defined, but rather characterized by the kernel function κ, defined as the inner product of two vectors: $\kappa(\mathbf{x}_i, \mathbf{x}_j) = \langle \Phi(\mathbf{x}_i), \Phi(\mathbf{x}_j) \rangle$. Commonly used kernels include the radial basis function (RBF) Gaussian kernel $\kappa(\mathbf{x}_i, \mathbf{x}_j) = \exp(-\|\mathbf{x}_i - \mathbf{x}_j\|_2^2 / \eta^2)$ with η used to control the width of the RBF, and order-d polynomial kernels $\kappa(\mathbf{x}_i, \mathbf{x}_j) = (\mathbf{x}_i \cdot \mathbf{x}_j + 1)^d$ [4, 5]. The algorithm to solve for (3) is modified from the algorithm of (2) with attentive manipulations of involving kernel functions.

We verify the effectiveness of the proposed methods via solving a classification problem on multi-sensor data focusing on discriminating between human and non-human footsteps. The experimental setup is as follows: a set of nine sensors including four acoustic (S_{1-4}), three seismic (S_{5-7}), one passive infrared (PIR) (S_8), and one ultrasonic (S_9) sensors are used to measure the same physical event simultaneously on the field. The ultimate goal is to detect whether the event involves human or human and animal footsteps. The system allows to evaluate the classification results based on various combinations of recording sources, not just multiple sensors of the same brands but also sensors of different signal types. For all methods, 15 combination sets of sensors are processed and compared, in which the first 9 sets are conducted using one single sensor separately, corresponding to S_1, S_2, ... S_9. The next 6 sets combine multiple sensors into various scenarios as listed in Table 1.

Our six proposed methods, which are based on different assumptions of the structures of coefficient vectors, noise/interference and linearity properties, are processed through all 15 sensor sets to determine the joint coefficient matrix $\mathbf{A}$ and class label is then determined by minimal error residua classifiers. The results are then compared with popular powerful techniques such as sparse logistic regression (SLR), heterogeneous feature machine (HFM), linear support vector machine (SVM), and their kernelized versions to verify the effectiveness of the proposed methods. The classification rates defined as ratios of the total number of correctly classified samples to the total number of testing samples, expressed as percentages, are plotted in Fig. 1 and Fig. 2, corresponding to testing data collected in December 09 and 10, respectively.

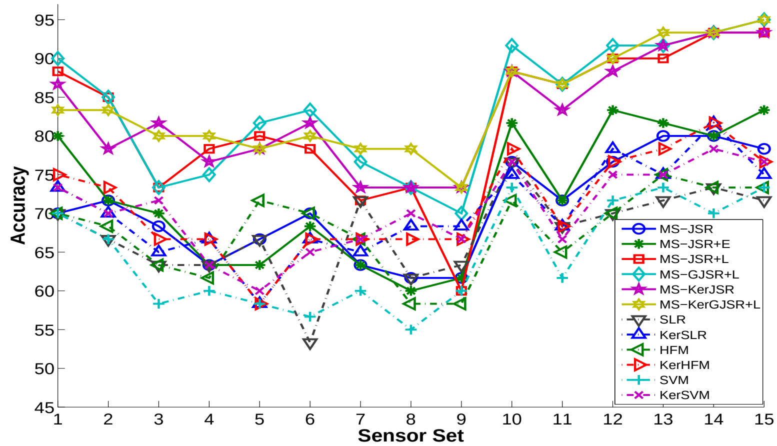

Figure 1: Comparison of classification results - DEC09

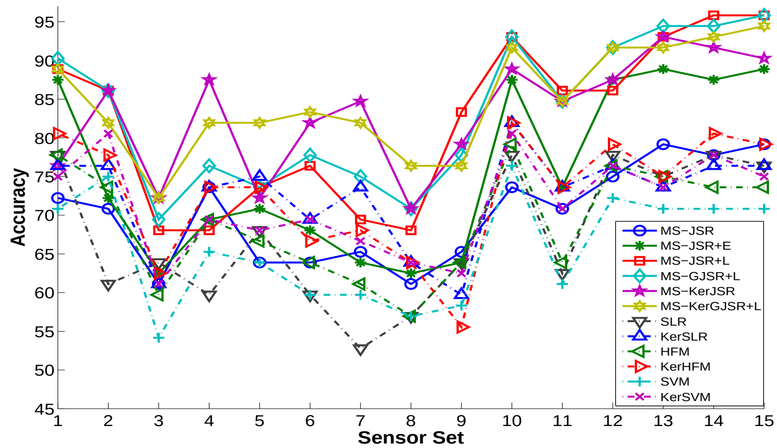

Figure 2: Comparison of classification results - DEC10

We tabulate the classification performance of all proposed models as well as competing methods in Table 2. The second and third columns in each table describe the classification accuracy by using single sensor and multiple sensors (which average the rates of sets 1-9 and 10-15, respectively), and the last column shows the overall results by averaging over all 15 sensor sets.

The experimental results with particular datasets show that our proposed models outperform the other conventional classifiers. These results also reveal several critical observations: *(1)* the use of complementary information from multiple sensors significantly improves the classification results over just using a singular sensor; *(2)* appropriate structured regularizations (joint and group sparsity) bring more advantage in selecting the right classes, hence increase the accuracy rate of classification results; *(3)* low-rank noise is a critical issue in multi-sensor fusion problem and *(4)* the classification in feature space induced by a kernel function yields a compelling performance improvement. Our proposed methods not only provide new tools, but also deepen the understanding of adaptive sparsity modeling, signal behavior and efficient multi-sensor data collection and collaboration. Nevertheless, although our techniques are designed for border patrol control in military purposes, they are not restricted to this specific application. Rather, they can be applied to any set of classification or discrimination problems, where the data is usually collected from multiple sources.

References

[1] J.-F. Cai, E. J. Candès, and Z. Shen, "A singular value thresholding algorithm for matrix completion," *SIAM Journal on Optimization*, vol. 20, no. 4, pp. 1956–1982, 2010.

Methods	Single sensor	Multiple sensors	Combine all sets
MS-JSR	66.30	77.22	70.67
MS-JSR+E	66.85	80.28	72.22
MS-JSR+L	76.48	90.28	82.00
MS-GJSR+L	78.70	**91.67**	**83.89**
MS-KerJSR	78.15	89.72	82.78
MS-KerGJSR+L	**79.44**	90.56	**83.89**
SLR	64.44	71.94	67.44
Ker-SLR	66.85	75.56	70.33
HFM	65.37	71.39	67.78
Ker-HFM	67.41	76.67	71.11
SVM	60.56	70.56	64.56
Ker-SVM	67.41	74.72	70.33

(a) DEC09

Methods	Single sensor	Multiple sensors	Combine all sets
MS-JSR	66.36	75.93	70.19
MS-JSR+E	68.98	85.65	75.65
MS-JSR+L	75.77	91.67	82.13
MS-GJSR+L	77.47	**92.36**	83.43
MS-KerJSR	79.01	89.35	83.15
MS-KerGJSR+L	**80.25**	90.74	**84.44**
SLR	62.65	74.54	67.41
Ker-SLR	69.91	76.39	72.50
HFM	65.90	73.61	68.98
Ker-HFM	69.14	78.24	72.78
SVM	62.65	70.37	65.74
Ker-SVM	68.52	75.69	71.39

(b) DEC10

Table 2: Classification results of single sensor sets, multiple sensor sets, and combining all sets.

[2] E. J. Candès, X. Li, Y. Ma, and J. Wright, "Robust principal component analysis?" *Journal of ACM*, vol. 58, no. 3, pp. 1–37, 2011.

[3] N. H. Nguyen, N. M. Nasrabadi, and T. D. Tran, "Robust multi-sensor classification via joint sparse representation," *IEEE International Conference on Information Fusion (FUSION)*, 2011.

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[5] B. Scholkopf and A. J. Smola, *Learning with kernels: support vector machines, regularization, optimization, and beyond.* MIT press, 2001.